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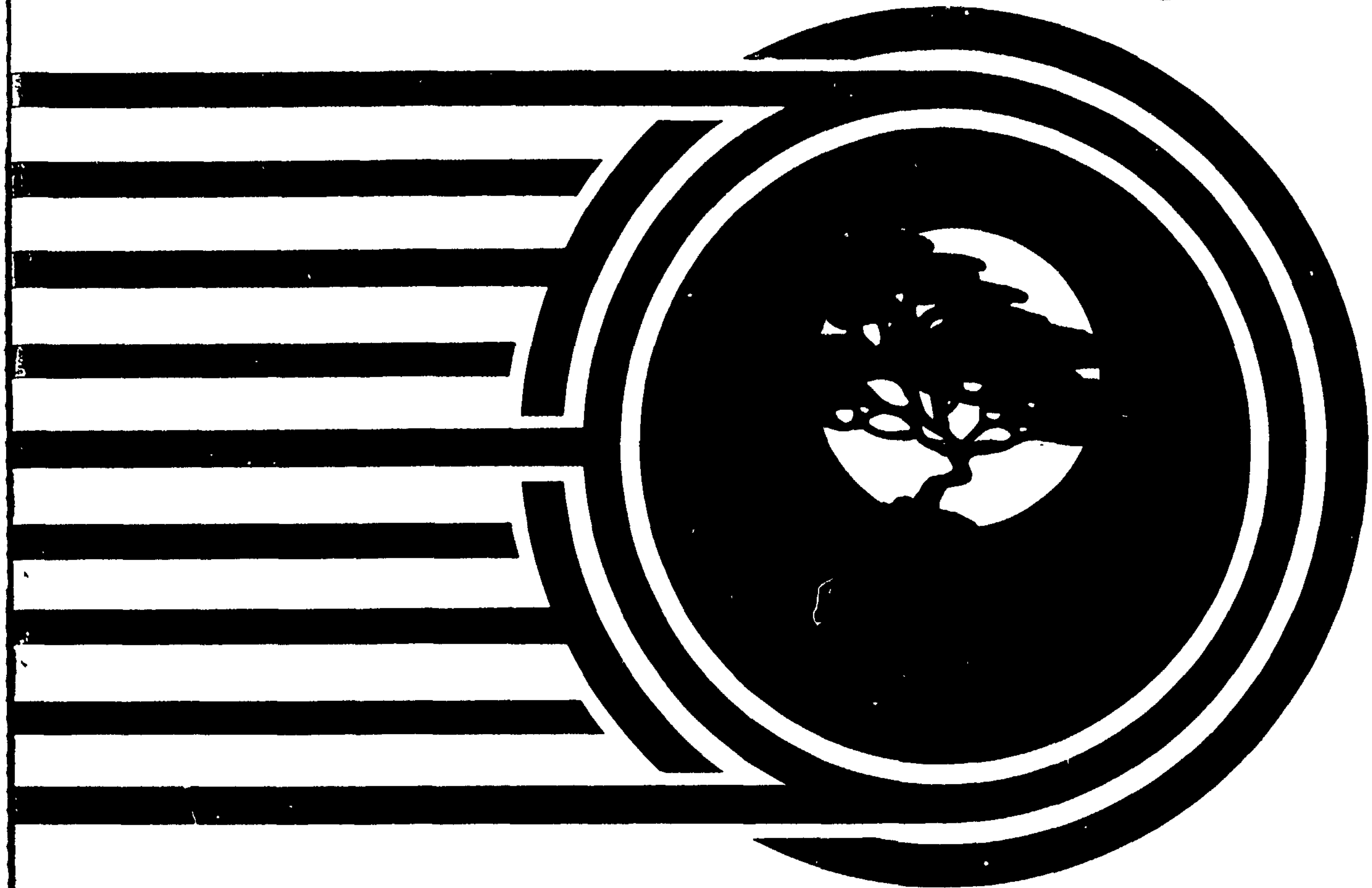

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PACT: POSSIBILISTIC APPROACH TO CORRELATION AND TRACKING

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ABSTRACT

A procedure is presented in this paper for treating the nongeolocational aspects of multi-target correlation and tracking based on the well developed calculi of possibility theory and certain new theoretical considerations. More generally, it is shown that a combination of possibilistic and probabilistic techniques leads to both a feasible and optimal parameter estimation algorithm. The technique incorporates observed data, error distributions-or equivalently, matching tables for attribute outcome values-and inference rules connecting attribute matching intensities with consequent correlation levels

1. INTRODUCTION

The multi-target multi-sensor target data association or "correlation" problem remains as one of the chief obstacles in constructing a comprehensive theory of surveillance. A survey of the state-of-the -art (unclassified) may be found in the Naval Ocean Surveillance Correlation Handbook (two editions)[1,2]. A good number of previous and present approaches to the correlation problem are based upon classical Bayesian statistical techniques. On the other hand, some approaches to the problem do rely upon heuristic procedures or mixtures of heuristic and statistical principles. (See again [1,2] for descriptions of these systems. In addition, see [3,4] for an excellent example of the total Bayesian approach.)

In any case, it appears that a large percentage of correlation problems involve vague or linguistic information which is not easy to model from a pure statistical viewpoint.

As an example of the above statements, consider the following four attributes which are commonly involved in informational inputs relative to tracking: A_1= class, A_2= frequency of signal at its source, A_3 = ship mode, and A_4 = geolocation with confidence ellipse. The natural domains of values of these attributes are typically: dom(A_1) =$\{C_1,..,C_m\}$, each C_k a label for a category of ship ; dom(A_2)= interval $[0,M_o]$, where M_o is some suitably chosen upper bound (in hz.); dom(A_3) = $\{D_1,..,D_n\}$, each D_k being a label for a mode of operation, noting the highly overlapping flavor in general possessed by the C_k's and D_k's, where some could actually represent subcategories with respect to others; dom(A_4)= $\{(p,E_p) \mid$ p any point in R^2, E_p any confidence ellipse centered at p ; each E_p has the same fixed probability level$\}$. Next, let i and j represent two fixed track histories. That is, each letter represents a collection of data from possibly several different sensor and intelligence sources which is assumed to correspond to the same (usually unknown) target source. This data may be classified into the four types of attributes mentioned above. In addition, it is assumed that error distributions - or equivalently, matching level tables- are obtainable for each of the types of observed data. Finally, it is assumed that prior known relations are available connecting the intensities of matches between any possible outcomes of attribute categorized data between i and j and consequential levels of correlation between i and j. Usually, the latter is in the form of inference rules. Both matching tables and inference rules may be obtained either analytically , using physics and geometrical constraints, or empirically, through the establishment of a panel of experts. The term "distribution" as used above may refer to classical probabilistic or possibilistic/fuzzy set definitions. (See [5] for a survey and summary of possibilistic distributions and properties.) Then, some statistic (in the general sense) is sought which will estimate the unknown correlation level between i and j , based upon the available data, matching tables, and inference rules.

The procedure presented in this paper is based upon three general theoretical types of results, obtained previously by the author:

(a) Fuzzy sets and their operators correspond in a natural way to random sets and their operators such that fuzzy set/possibilistic modeling in effect is a weakened form of probabilistic modeling, thus allowing for interchange between the two types of modeling. This result leads to the procedure where all input information to the correlation problem is converted seperately to possibilistic forms connected by ordinary (two-valued) logical relations-usually, conjunction. Then, following the application of the algorithm (described below) , the initial outputs in possibilistic form are reconverted to probabilistic form, if desired. (See [6] and [7].)

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(b) Given input information consisting of an ordinary logical combination of possibilistic descriptions of an unknown parameter vector, a uniformly most accurate pure possibilistic description exists which is obtainable by replacement of all ordinary connectors by corresponding (appropriate) fuzzy set ones. This description can be shown, under sufficient conditions, to yield an asymptotically consistent estimator of the parameter in question, with computable error bounds involving the original description and the pure possibilistic one. This result forms the basis of the structure of PACT. (See [8]; [9], sect. D.)

(c) Under very general conditions, conditional fuzzy sets may be constucted, analagous to conditional random variables. In turn, this leads to a possibilistic version of Bayes theorem. (See [9], [10].) Then, with the identification of inference rules with posterior parameter distributions (and matching table forms with posterior data distributions), it can be shown that the output description of the correlation (the unknown parameter here) as established in result (b) is essentially the same as the posterior distribution of the correlation in the possibilistic Bayesian sense. (See [11].)

2. GENERAL DIAGNOSTIC SYSTEMS

Before exhibiting the structure (b) of the PACT algorithm, we will consider a more general diagnostic system which encompasses not only the PACT algorithm, but other applications, including classification, system diagnosis, and medical daignosis techniques.

Let attributes $A_1, A_2, \ldots, A_m$ be m types of information over which observed data $\mathring{Z}$ can be categorized. Thus we write in partitioned form

$$\mathring{Z} = \begin{pmatrix} \mathring{Z}_1 \\ \vdots \\ \mathring{Z}_m \end{pmatrix} \tag{1}$$

where $\mathring{Z}_k$ is observed from the domain of A_k, $\mathrm{dom}(A_k)$, for $k=1,\ldots,m$. It is assumed $\mathrm{dom}(A_k)$ is known. Corresponding to $\mathring{Z}_k$ we denote as a variable Z_k any possible value $\mathring{Z}_k$ could have taken in $\mathrm{dom}(A_k)$; similarly for Z.

Let Q denote the unknown parameter vector of interest. Denote the matching table (or by a simple transform, the error distribution) for attribute A_k by M_k. Typically, M_k is evaluated as a number between 0 and 1:

$$0 \le M_k(\mathring{Z}_k, Z_k) \le 1 \quad . \tag{2}$$

Define symbolically R_t to correspond to the t^{th} fuzzy relation connecting any Z with Q. Specifically,

$$R_t : \bigtimes_{v=1}^{h_t} \mathrm{dom}(A_{k_v}) \times \mathrm{dom}(Q) \longrightarrow [0,1], \tag{3}$$

where $1 \le k_1 < k_2 < \cdots < k_{h_t} \le m$ represents the collection of attributes involved in the t^{th} relation R_t. Typically, R_t is evaluated (clearly, as a membership function) as a number between 0 and 1:

$$0 \le R_t(Z,Q) \le 1 \quad , \tag{4}$$

with some abuse of subscript notation. Note that formally M_k and R_t are possibility distributions (or equivalently, fuzzy set membership functions)

We may think of M_k corresponding to the following linguistic description:

$$M_k(\mathring{Z}_k, Z_k) = \text{possibility that } Z_k \text{ is the true value, when data } \mathring{Z}_k \text{ is observed, noting both } Z_k \text{ and } \mathring{Z}_k \in \mathrm{dom}(A_k). \tag{5}$$

Similarly, we may interpret

$$R_t(Z,Q) = \text{possibility that } Z \text{ (through attributes } A_{k_1},\ldots,A_{k_{h_t}}) \text{ and } Q \text{ are related.} \tag{6}$$

Theorem 1. Uniformly Most Accurate Estimators

Suppose that information concerning unknown parameter Q consists of the following forms:

(i) Data $\mathring{Z}$.
(ii) Matching tables M_k, $k=1,\ldots,m$.
(iii) Relations R_t, $t=1,\ldots,r$.

Let $g: \underbrace{[0,1] \times \cdots \times [0,1]}_{(m+r \text{ factors})} \longrightarrow [0,1]$ be nondecreasing with respect to the partial ordering of vectors. In particular, g can be any t-norm, the natural operator corresponding to conjunction ("and") (see [7]).

Define the possibility distribution Φ by

$$\Phi(Q \mid \mathring{Z}) \stackrel{d}{=} 1 - \underset{(\text{all } Z)}{g}(1 - C(Z,\mathring{Z},Q)) \ , \tag{7}$$

where it is assumed g is extendable to an arbitrary number of arguments (this is guaranteed if, e.g., g is symmetric and associative, which will be the case if g is a t-norm) , and

$$C(Z,\mathring{Z},Q) \stackrel{d}{=} g(R(Z,Q), M(\mathring{Z},Z)) \ , \tag{8}$$

$$M(\mathring{Z},Z) \stackrel{d}{=} \underset{(k=1,\ldots,m)}{g}(M_k(\mathring{Z}_k,Z_k)) = \text{matching table effect under } g \ , \tag{9}$$

$$R(Z,Q) \stackrel{d}{=} \underset{(t=1,\ldots,r)}{g}(R_t(Z,Q)) = \text{relation effect under } g \ , \tag{10}$$

and Q is arbitrary $\in \mathrm{dom}(Q)$.

For any confidence levels

$$\underset{\sim}{\alpha} \overset{d}{=} (\alpha_1, \alpha_2, \ldots, \alpha_m) \quad , \tag{11}$$

$$\underset{\sim}{\beta} \overset{d}{=} (\beta_1, \beta_2, \ldots, \beta_r) \quad , \tag{12}$$

with α_k, $\beta_t \in [0,1]$, all k,t, define the <u>original hypothesis set</u> as

$$H_o(\underset{\sim}{\alpha}, \underset{\sim}{\beta}; g) \overset{d}{=} \{\binom{Q}{Z} \mid \overset{r}{\underset{t=1}{\&}} (R_t(Z,Q) \geq \beta_t) \; \& \; \overset{m}{\underset{k=1}{\&}} (M_k(\mathring{Z}_k, Z_k) \geq \alpha_k)\}. \tag{13}$$

Then (for $\mathring{Z}$ fixed), for any possibility distribution $D(\binom{Z}{Q} \mid \mathring{Z})$ as a function of Q over dom(Q), Z over dom(Z), yields the smallest set

$$\{\binom{Z}{Q} \mid D(\binom{Z}{Q} \mid \mathring{Z}) \geq g(\underset{\sim}{\alpha}, \underset{\sim}{\beta})\} \supseteq H_o(\underset{\sim}{\alpha}, \underset{\sim}{\beta}; g), \tag{14}$$

simultaneously for all possible $\underset{\sim}{\alpha}$ and $\underset{\sim}{\beta}$, when D is chosen

$$D(\binom{Z}{Q} \mid \mathring{Z}) = C(Z, \mathring{Z}, Q) \quad , \tag{15}$$

for all $Z, \mathring{Z}, Q$. In turn, Φ enjoys a similar property with respect to the <u>projection</u> 1-g(1-·) applied to H_o and D.

(For proofs, see [9], section 10.) ■

Thus, the above theorem exhibits in a general setting the uniformly most accurate single fuzzy set description of Q, given $\mathring{Z}$ and g. The next theorem justifies the result outlined in (c) above.

<u>Theorem 2.</u> Posterior Form for Optimal Estimator

Suppose the same conditions holds as in Theorem 1. Then Φ as given in eq.(7) is the posterior possibilistic distribution of Q given $\mathring{Z}$ (see [11]) where the following identifications are made:

$$M(\mathring{Z}, Z) = \text{poss}(Z \mid \mathring{Z}), \tag{16}$$

$$R(Z,Q) = \text{poss}(Q \mid Z) \quad , \tag{17}$$

and the sufficiency condition

$$\text{poss}(\ (Q \mid \mathring{Z}) \mid (Z \mid \mathring{Z})) = \text{poss}(Q \mid Z) \quad , \tag{18}$$

holds for all $Z, \mathring{Z}, Q$, and "poss" refers to any possibility function (conditional form) constructed in accordance with its corresponding variables, using possibilistic Bayes Theorem ([11]).

(Proof: Simply use the relations

$$\text{poss}(\binom{Q}{Z} \mid \mathring{Z}\ ) = \text{poss}\left(\begin{pmatrix}(Q \mid \mathring{Z})\\(Z \mid \mathring{Z})\end{pmatrix}\right)$$

$$= g(\ \text{poss}((Q \mid \mathring{Z}) \mid (Z \mid \mathring{Z}))\ ,\ \text{poss}(Z \mid \mathring{Z})) \tag{19}$$

and then apply the projection operator to both sides with respect to variable Z.) ■

For justification for the results in (a), see [11], the sections on background of fuzzy set systems and connections between fuzzy set systems and random set systems.

3. <u>APPLICATIONS TO SPECIFIC SYSTEMS</u>

I. <u>Medical Diagnosis</u> / <u>Classification</u>

In this situation, attributes = symptoms, the fuzzy relations are obtained from empirical evidence, while the matching tables are obtained from either analytic or empirical means. The fuzzy relations refer to any given patient's symptoms and their relations to his possible disease, the unknown parameter here. Thus, dom(Q) here consists of the possible diseases of relevancy, with the possible addition of a value "not known yet-keep testing". See for example [12] for an Artificial Intelligence approach to medical diagnosis and [13] for a similar (but not justified through use of results similar to Theorems 1 or 2) fuzzy set approach. Classification differs formally little from the above application. (However, this differs considerably from other fuzzy set approaches to classification such as Bezdek's [14].)

II. <u>Correlation Problem</u>

Consider first a set of confusable track histories {1,2,..,q}, say. Pick out any i ≠ j, and define, omitting the obvious subscript dependency,

$$Q \overset{d}{=} \text{poss}(\text{ i and j correlate, i.e., belong to the same target source}), \tag{20}$$

Let all of the fuzzy relations here be of the form of <u>inference rules</u>. Thus, linguistically, a typical R_t corresponds to the phrase

"<u>If</u> a match between i and j occurs relative to attribute A_{k_1} to intensity level α_{k_1} and,..., and
a match between i and j occurs relative to attribute $A_{k_{h_t}}$ to intensity level $\alpha_{k_{h_t}}$,

<u>then</u> i and j correlate to intensity $f(\underset{\sim}{\alpha}_t)$",

where $f(\underset{\sim}{\alpha}_t)$ is a number between 0 and 1 and $\underset{\sim}{\alpha}_t$ is the vector of α_k's; in general, both of these values are obtained from a panel of experts. The intensities of the attribute matches is most easily translated by an exponentiation process applied to the appropriate attribute matching functions. A simple conversion table between the degree of matching, expressed linguistically or initially numerically on a scale from 0 (no match) to 0.5 (normal match) up to 1.0 (complete match), might be established by use of the relation

$$((x)) \overset{d}{=} x/(1-x) \quad , \tag{21}$$

for all $x \in [0,1]$, where ((x)) is to be used as an exponent. Other translations of the intensities of matches are of course possible and may be more appropriate, following empirical studies. (Future work will consider this problem. See also Dubois and Prade [5], pp. 256-264 for similar problems.)

Combining all of the above remarks, a reasonable possibilistic model for inference rule t is

$$R_t(Z,Q) = \Psi_{*}(G_t(Z),\ Q((f(\alpha_t)))), \qquad (22a)$$

$$G_t(Z) \overset{d}{=} \underset{(v=1,..,n_t)}{g}\left(M_{k_v}(Z_{k_v}^{(i)}, Z_{k_v}^{(j)})((\alpha_{k_v}))\right), \qquad (22b)$$

$$\Psi_{*}(x,y) \overset{d}{=} 1-g(x,1-y) \qquad (22c)$$

In this case, data vector $\mathring{Z}$ (and similarly for variable Z) is broken up into the i-data and j-data, as indicated by the appropriate superscript, with the previous notation still holding for the attribute indices.

A summary of the PACT algorithm is given below in Fig. 1 :

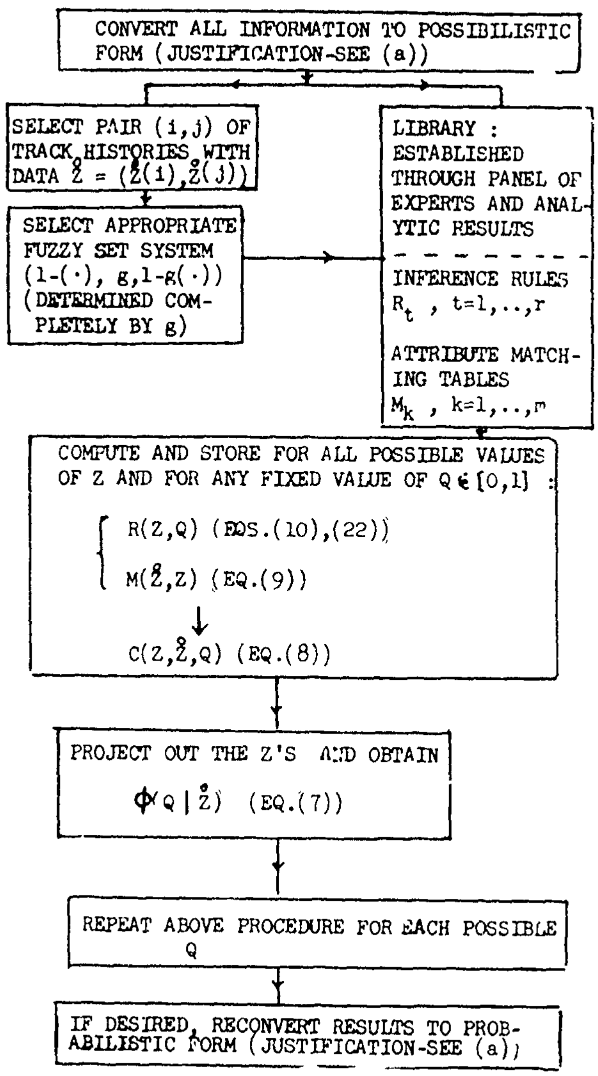

Fig. 1 Outline of the basic correlation algorithm.

4. CONCLUSIONS

Based on three general results ((a),(b),(c)), an algorithm has been developed which treats the multiple target correlation problem, including data categorized as nongeolocational. Figure 1. succinctly summarizes the structure of the algorithm, which depends functionally on the collection of relevant inference rules chosen as well as the attribute matching tables.

A number of problems have arisen in the implementation of the PACT algorithm:

(i) How should attributes be chosen? What systematic procedures are available for determining from available experts and other informational sources what are the most important and distinct attributes to consider. Novakowska's clustering-like approach [15] or alternatively a modified factor anaysis approach might lead to satisfactory choices.

(ii) In utilizing a panel of experts, the way questions are formulated is critical. Consequently, use of questionnaire and psychometric techniques to extract maximal unbiased information is necessary.

(iii) Perhaps the most critical problem is the actual determination of the inference rules. Even with a relatively few attributes used as a basis, there are myriad combinations of possible intensities of attribute matches leading to the corresponding inference rules. Thus, a method is needed to generate inference rules which are relatively distinct (too many redundant-like rules will cause unnecessary computer running time without adding much information content). Can a metric be designed which determines the amount of "distinctness" between rules? The answer to these problems may well lie within the purview of Artificial Intelligence techniques or related search theory procedures.

(iv) Complete flow charts for the PACT algorithm in its general form have been made (and are available to interested readers upon request). Preliminary numerical runs indicate a long running program. Consequently, by utilizing the basic bounding property of t-norms and t-conorms (see , e.g., [9], section 4) , an algorithm may be obtained which is simpler in form than the original PACT algorithm and which yields as outputs lower bounds to the posterior correlation distribution:

$$\Phi(Q \mid \mathring{Z}) \geq \Phi_{LB}(Q \mid \mathring{Z}) , \qquad (23)$$

$$\Phi_{LB}(Q \mid \mathring{Z}) = \max(\ G(\mathring{Z}),\ R''(Q)) , \qquad (24)$$

$$G(\mathring{Z}) = \underset{(\text{all } Z)}{1-g}(1-F(\mathring{Z},Z)) , \qquad (25)$$

$$F(\mathring{Z},Z) = g(\ R'(Z), M(\mathring{Z},Z)), \qquad (26)$$

$$R'(Z) = \underset{(t=1,..,r)}{g}(1-G_t(Z)) , \qquad (27)$$

$$R''(Q) = \underset{(t=1,..,r)}{g}(Q((f(\alpha_t)))) . \qquad (28)$$

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